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Robust optimization of manufacturing systems flexibility

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Abstract

Mass customization requires frequent product changeovers thus leading to the need of manufacturing systems endowed with flexibility and reconfiguration capabilities, in order to be robust to changes in the production scenario. Therefore, manufacturing companies face a relevant risk when taking strategic decisions about which system resources should be acquired. This risk can be mitigated by exploiting performance evaluation models, such as analytical models and Discrete Event Simulation, that are effectively adopted to estimate the performance of possible system configurations. However, current decision-support tools for optimizing system configurations can be only loosely coupled with performance evaluation models, hence undermining the actual optimization of the system itself, even more if production requirements may evolve in the future. This work presents an analytical methodology to support the optimization of manufacturing systems configuration and reconfiguration subject to evolving production requirements. The methodology integrates a stochastic analytical model for performance evaluation of manufacturing lines into a mixed integer programming problem, by means of performance linearization. The advantage of using the proposed methodology is shown on a line configuration problem, where buffer capacities and machine capabilities have to be jointly optimized, in order to minimize costs and satisfy the target performance.

Keywords: Manufacturing system, Robust optimization, Flexibility, Variability.

1. Introduction

Mass customization requires frequent product changeovers thus leading to the need of manufacturing systems endowed with flexibility and reconfiguration capabilities, in order to be robust to changes in the production scenario. Therefore, manufacturing companies face a relevant risk when taking strategic decisions about which system resources should be acquired.

Serial lines are among the most adopted configurations in manufacturing companies [1]. A serial line is a manufacturing line composed of a series of stages, each of them performing one or more operations to the product, which may be decoupled by inter-operational buffers. Highly automated lines are characterized by fast repeatable operations, which make this type of lines very efficient, but also very sensitive to any occurring disruptive event in one stage, which then propagates its effect along the stages.

Recent technological developments pushed the design of serial lines taking advantage of modularity to enable easy reconfiguration of the system. Therefore, a modern serial line may undergo several configuration optimization decisions along its lifecycle. Configuration decisions include a wide variety of aspects, such as buffer capacity and allocation, machine capability selection, machine cycle time balancing. Each decision may represent a constraint for the future and limit the company competitiveness. In this context, volume flexibility may guarantee to the company a certain degree of flexibility in proactively addressing production changes [2]. In order to assess the volume flexibility, the system performance should be evaluated in an accurate way and the configuration decisions optimized efficiently.

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The aim of this work is to present an analytical methodology to support the optimization of manufacturing systems configuration. The overall methodology integrates an analytical stochastic model for the performance evaluation of manufacturing systems into a mixed integer linear programming problem, by means of performance linearization.

The paper is organized as follows. A brief review of related works is provided in the following subsection, then the methodology is presented in Section 2 and numerical results are shown in Section 3. Section 4 concludes the work and suggests future research.

1.1. Related works

The optimization of manufacturing systems aims at the optimization of system performance with respect to a user-defined objective function, usually a cost function, depending on specific decision variables. Normally, the productivity of the system configuration (i.e. throughput) is among the main system performance measures of interest include. The decision variables may include a wide range of decisions, from the buffer capacity to the stage cycle time, to the machine capability in terms of reliability and maintainability, which can be represented by proxy as the Mean Time to Failure (MTTF) and the Mean Time to Repair (MTTR). However, it must be noted that all the system performance measures (e.g. throughput, average work-in-progress, system lead time), do not vary linearly with respect to the change in system parameters [3].

Performance evaluation tools, such as analytical models and Discrete Event Simulation, estimate the performance of possible system configuration by taking into account the stochastic dynamics and propagation of effects and therefore they can efficiently support the companies in the configuration phase [4].

Optimization methods for supporting decisions are usually loosely coupled with performance evaluation models. In general, optimization is carried out through iterative procedures by keeping the evaluation module independent from the optimization module, and having the two modules exchanging iteratively input and output [5,6].

Optimization methods based on linear programming normally consider the performance evaluation of the system as linear with respect to the varying parameters, hence introducing much approximation in the real performance metrics [7,8]. On the other hand, if accurate performance evaluation models are used, black-box heuristics are usually preferred thus leading to near-optimal or sub-optimal solutions. This can jeopardize the final configuration decision, and therefore the investment done by the company. Only few works exploit the properties of the evaluation model to improve the optimization efficiency and integrate it into a unique framework [9].

Table 1 reports a few works addressing the optimization of single-product type manufacturing lines. The works are classified according to the decision variables, the performance evaluation method, the optimization method, and the integration between performance evaluation and optimization.

In literature, according to the decision variables for the configuration optimization, different methodologies are applied. One of the most treated problem related is the Buffer Allocation Problem (BAP), for which a recent review of methodologies and solutions can be found in [10]. A limited number of works treat simultaneously the joint optimization of buffer capacity and production stage characteristics. However, companies often seek for a wider perspective that considers also the determination of the cycle time of each stage and then

Table 1. Classification of relevant papers for the optimisation of manufacturing systems.

	Decision variables					Configuration evaluation method	Optimization method	Relation between performance evaluation and optimization
	Buffer capacity	Stage cycle time	Machine selection	MTTR	MTTF			
Spieckermann (2000)	X	X				Simulation model	Genetic algorithm	Iterative
Goyal (2012)		X				Linear performance	NSGA II	Integrated
Yegul (2017)	X (only a sub-set)	X (only a sub-set)		X (only a sub-set)	X (only a sub-set)	Simulation model	Ant-colony with myopic search	Iterative
Pedrielli (2018)	X	X				Simulation model	Math-heuristics for the approximated LP	Integrated (DEO)
Moghaddam (2018)		X				Linear performance	MILP	Integrated
Nahas (2018)	X		X	X		Approximate analytical model	Heuristics (GA, NTA, ant-colony)	Iterative
Xi (2019)	X					Decomposed open queuing network (M/G/c/K)	Decomposition-Coordination Method + LRS	Independent sub-problems

the consequences on the buffer allocation [11]. This is because the problem is extremely complex with respect to the number of decision variables. As a consequence, researchers who focus on optimization methodologies, usually make simplified assumptions in the performance evaluation, i.e. they consider the system performance as linearly varying with respect to the system parameters. On the other hand, researchers who adopt more accurate performance evaluation methods, integrate the configuration evaluation in the overall optimization model through an iterative approach.

In this work, an integrated approach is proposed, aiming at exploiting the mathematical properties of the performance measures with respect to the buffer capacity and the Mean Time to Failure.

2. Methodology

The proposed methodology integrates a stochastic analytical model for performance evaluation of serial manufacturing lines into a mixed integer programming problem, by means of performance linearization. The graphical representation of the proposed algorithm is shown in Figure 1.

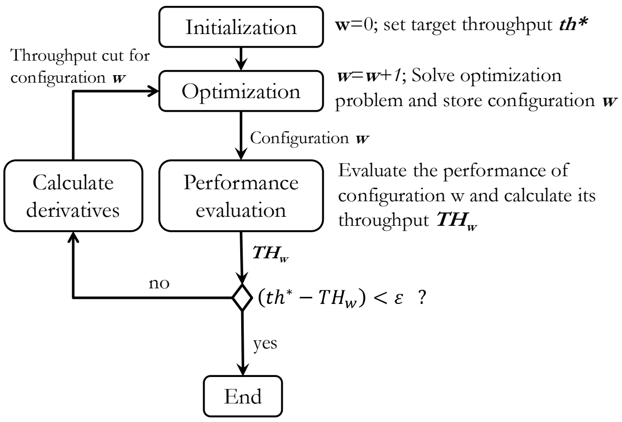

Figure 1. Graphical representation of the algorithm.

The algorithm starts with the initialization and setting of the target throughput (th^*). The iterative loop of the algorithm consists of the optimization of the configuration including an estimate of the throughput thanks to an approximation based on linear constraints. The candidate configuration obtained as result of the optimization problem is given as input to the performance evaluation model for an accurate estimation of the throughput. The algorithm proceeds iteratively until convergence, i.e. when the throughput estimated by the performance evaluation is greater or equal to the target throughput, while considering a tolerance. If convergence is not reached, then first-order derivatives are extracted from the performance evaluation model and used to generate a constraint (*throughput cut*) linearizing the performance that is added to the optimization problem.

The following subsection provides a brief introduction to the performance evaluation module, then in Section 2.2 the optimization problem is presented and discussed. Notation, including parameters and decision variables of the optimization problem, are shown in the following text box.

Notation	
i	production stage ($i = 1 \dots I$)
j	MTTF type ($j = 1 \dots J$)
k	buffer ($k = 1 \dots I-1$)
w	algorithm iteration that is associated with a candidate system configuration w
Parameters	
c_k	unit capacity cost for buffer k
d_j	cost of MTTF type j
m_i	production rate of production stage i
r_i	repair rate of production stage i
f_j	MTTF of type j
$h_{i,j} \in \{0,1\}$	equal to 1 if MTTF type j can be assigned to production stage i, 0 otherwise
th^*	target throughput
$thmax$	maximum throughput
TH_w	throughput of configuration w estimated by performance evaluation model
$yn_{k,w}$	capacity of buffer k in configuration w
$yf_{i,w}$	mean time to failure in production stage i of configuration w
$dTHdb_{k,w}$	derivative of throughput with respect to capacity of buffer k of configuration w
$dTHdf_{i,w}$	derivative of throughput with respect to mean time to failure in production stage i of configuration w
ε	algorithm convergence tolerance
Decision variables	
$x_{i,j} \in \{0,1\}$	equal to 1 if MTTF type j is selected for production stage i, 0 otherwise
$xn_k \in \mathbb{N}$	capacity of buffer k that is placed downstream of production stage i
$xf_i \in \mathbb{R}^+$	mean time to failure in production stage i
$THapp \in \mathbb{R}^+$	estimated throughput based on the linear approximation

2.1. Performance evaluation model

The stochastic analytical model for the performance evaluation of serial lines decoupled by finite-capacity buffers has been introduced in [12]. In Figure 2, the manufacturing serial line is shown, where blue squares represent machines and yellow circles represent buffers. Each machine is characterized by production rate m, failure rate $1/f$ and repair rate r.

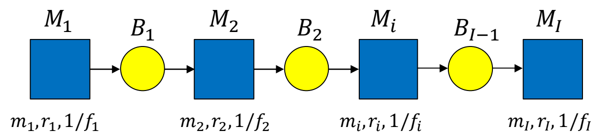

Figure 2. Graphical representation of the manufacturing line.

Decomposition equations based on the system dynamics model the propagation of effect, i.e. blocking and starvation, along the stages. A linear system of differential equations is solved by a numerical algorithm in order to evaluate the system performance in terms of throughput, average buffer level and steady-state probabilities.

The advantage of using an analytical model is that the explicit relation between input parameters and output performance can be obtained. Based on this model the first derivatives of the system throughput can be derived. The derivatives are then used to write the first-order approximation of the throughput with respect to the system parameters. In fact, as explained in the previous section, performance measures such as system throughput do not depend linearly on the system parameters. For instance, let us consider the throughput variation with respect to the buffer capacity *N*, which is shown in Figure 3. If the first derivative of the throughput with respect to buffer capacity is known in a certain point (th_0,n_0), the tangent line to a given point can be written as:

$$th_{lin} = \frac{\partial th}{\partial n_0}\left(n - n_0\right) + th_0$$

Therefore, the linear approximation of the throughput curve increases the accuracy for each tangent line added to the set, as shown in Figure 3.

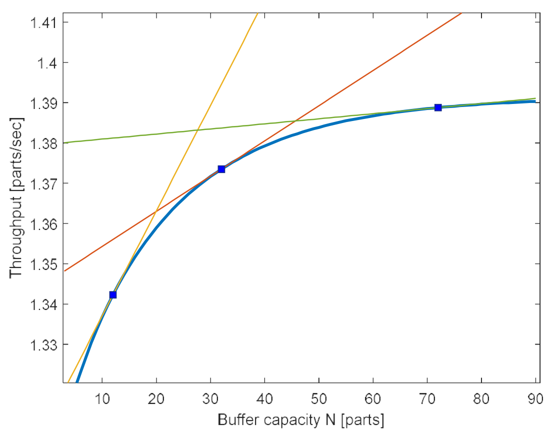

Figure 3. Throughput as a function of buffer capacity with first-order linearization.

2.2. Optimization model

The optimization model is formulated as a Mixed-Integer Linear Problem (MILP). The goal is to minimize the overall cost (1) given by the purchase of machines and buffer slots, while satisfying the target throughput (2). An upper bound for the throughput (3) can be calculated thanks to a preliminary analysis of the problem. One machine type must be chosen for each production stage (4) among the feasible ones (5). Given the choice of machine type it is possible to calculate the actual mean time to failure (6) for each production stage. Finally, constraint (7) represents the throughput cut that is added after each iteration based on the linearization of the throughput.

$$\min\left(\sum_k c_k \cdot xn_k + \sum_{i,j} d_j \cdot x_{ij}\right) \tag{1}$$

$$THapp \geq th^* \tag{2}$$

$$THapp \leq thmax \tag{3}$$

$$\sum_j x_{i,j} = 1 \qquad \forall i \tag{4}$$

$$x_{i,j} \leq h_{i,j} \qquad \forall i,j \tag{5}$$

$$xf_i = \sum_j f_j \cdot x_{i,j} \qquad \forall i \tag{6}$$

$$THapp \leq TH_w + \sum_k dTHdb_{k,w} \cdot \left(xn_k - yn_{k,w}\right) + \sum_i dTHdf_{i,w} \cdot \left(xf_i - yf_{i,w}\right) \qquad \forall w \tag{7}$$

3. Case study

The approach introduced in the paper has been used to evaluate the optimal improvement strategy in a real manufacturing line.

The reference case has been described in [13]. The company is an Italian manufacturer that produces drawers for personalized kitchens. The sides of the drawers are assembled by the production line shown in Figure 4, having a high level of automation. Four stages can be identified in the line. Linear guiderails serve as buffers in the line, where the capacity is given by the total length.

The first two stages (stages M1 and M2) assembles components to the main body of the drawer. The second part of the line (stages M3 and M4) welds the components to the body and performs some final operations including a visual quality check, though parts are not scrapped within the line.

The company needs to increase the throughput of 30% in order to satisfy the customer requirements. Therefore, they investigated the possible improvement actions to be implemented on the line.

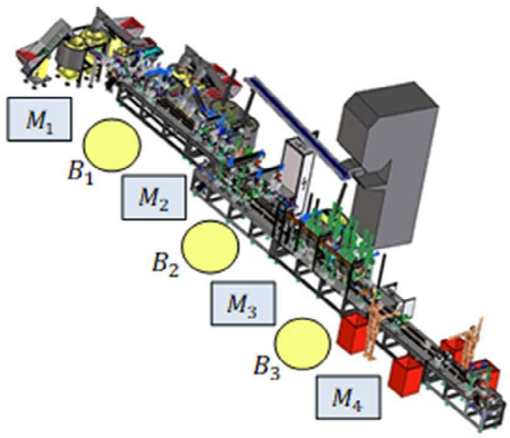

Figure 4. Multi-stage manufacturing line producing drawers (courtesy of Cosberg).

The complete set of possible actions is provided in Table 2. In total, 5 machine configurations can be tested, which includes the base case (not implementing any action) and the four improvement actions. Each action has a different impact on the Mean Time to Failure, however, the overall impact on the system performance such as the throughput is not known in advance. In this case, a Predictive Maintenance (PM) strategy is tested, in order to select the right combination of station components for which the PM strategy should be implemented. These actions can be quite costly because they imply the installation of sensors for the data gathering of the selected component, such as the actuators or the fixtures, and the development of an ad hoc software architecture for the PM actuation. Therefore they might have a relevant impact on the company budget.

On the other hand, the increase of buffer capacity might be a less expensive solution if some flexibility had been acquired already as in this case. In fact, stations in the manufacturing line can be moved along the linear guidelines that serve as buffers, and therefore the buffer capacity along the line can be changed to some extent by only increasing or decreasing the distance between stations. However, the space which had been allocated to the manufacturing line represents a constraint on the total buffer capacity which is added to the optimization problem.

3.1. Results and discussion

The optimization algorithm has provided the solution in 10 iterations. The optimal solution consists of implementing actions A3 on station M1 and action A4 on station M2, while reducing the buffer capacity of the all buffers to be equal to 3 parts. The objective function per iteration is shown in Figure 5.

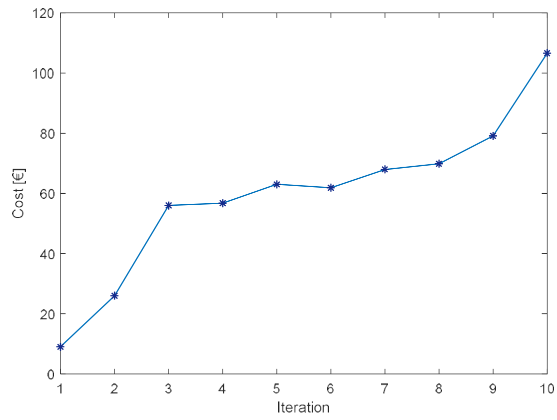

Figure 5. Objective cost function per iteration.

Figure 6 shows the system configurations that are tested in each iteration, with respect to the buffer capacities (Figure 6a), and to the Mean Time to Failure, i.e. the selected components for the implementation of the PM strategy in each machine

Table 2. Parameters of the optimization problem for the industrial use-case.

Station	Current configuration	Action	Cost	Influence on parameters
M1	f=111 min	A1: PM on one component	40.42 k€	f=133 min
		A2: PM on two components	42.94 k€	f=180 min
		A3: PM on three components	47.72 k€	f=430 min
		A4: PM on four components	49.08 k€	f=666 min
B1	N1 = 4 parts	Change buffer capacity		N1
M2	f=31 min	A1: PM on one component	44.64 k€	f=66 min
		A2: PM on two components	46.97 k€	f=117 min
		A3: PM on three components	48.66 k€	f=238 min
		A4: PM on four components	49.86 k€	f=769 min
B2	N2 = 5 parts	Change buffer capacity		N2
M3	-	no		-
B3	N3 = 7 parts	Change buffer capacity		N3
M4	-	no		-
Additional constraint		Maximum buffer capacity		N1+N2+N3<30
Current throughput = 6.6 parts/min			**Target throughput = 9 parts/min**	

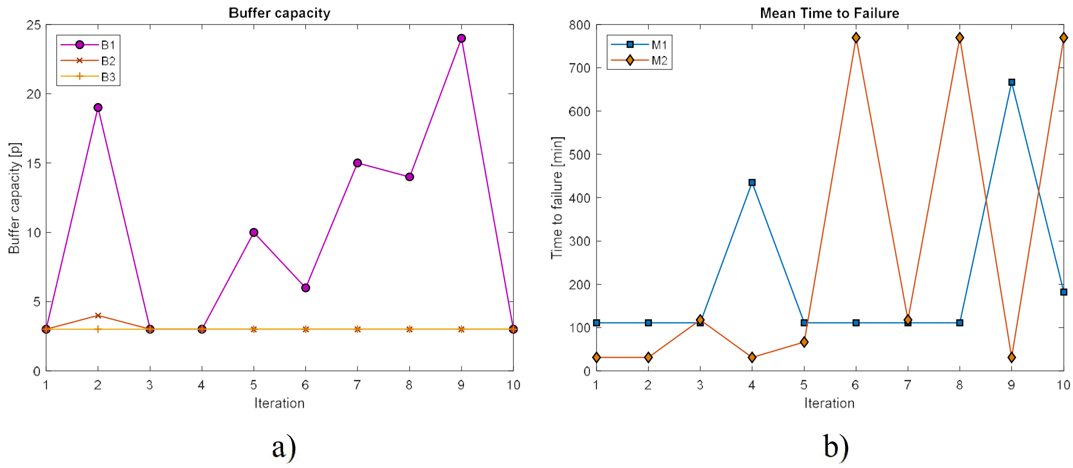

Figure 6. System parameters per iteration: Buffer Capacity (a) and Mean Time to Failure in each machine (b).

(Figure 6b). Given the cost function, the optimization algorithm provides iteratively the less expensive solution, which means not implementing any PM strategy and trying to increase the throughput by increasing the buffer capacity allocated to the line. This can be noticed in Figure 6b where the Mean Time to Failure of both machines M1 and M2 does not change in the iterations 1 and 2, while the buffer capacities N1 and N2 do change in Figure 6a. However, these alternatives are found not feasible and therefore are discarded until the optimal solution is found. As a result, Figure7 shows the throughput that has been evaluated at each iteration to reach the target throughput (horizontal line). Despite a general increasing trend, it is interesting to notice that the throughput function might be not in trade-off with the cost function.

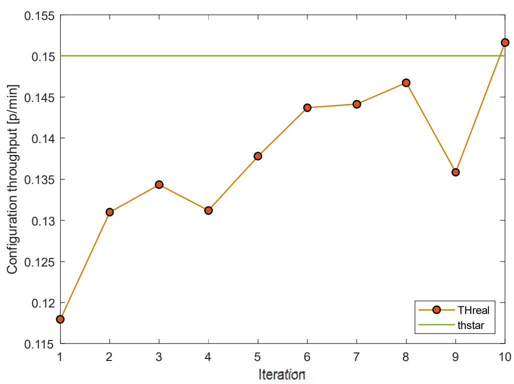

Figure 7. System throughput per iteration.

4. Conclusion

This work has introduced an integrated approach for the optimization of stochastic manufacturing systems, where a decision-support tools for optimizing system configurations is coupled with an analytical performance evaluation model in order to provide fast and robust solutions.

Future research will focus on the generalization of the approach for addressing different types of system parameters and manufacturing problems, such as line balancing and buffer allocation. The methodology will be compared with other existing ones, in order to highlight the advantages.

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